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Web-Based Application for Plant Leaf Disease Detection

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Abstract: - Several diseases that affect plant leaves pose a severe hazard to agriculture. Our approach identifies both the disease that harmed the leaf and the area of harm. Crop diseases, especially those that predominantly affect the leaves, have an impact on both the quantity and quality of agricultural output. The objective of the article is to raise consciousness among farmers about the latest innovations that can prevent disease of plant leaves. The techniques of data mining and image processing with an accurate algorithm have been identified to detect leaf illnesses in the potato plant as potatoes are only an easily accessible vegetable. In this study, we present a web-based automated approach for identifying and classifying plant leaf diseases. The recommended approach involves receiving an input image, delivering it to the model using a Postman API, analyzing the image using a CNN model kept inside a Docker container, and producing a result to determine if the image is classified as healthy or unhealthy. The Plant Village dataset for plants like tomatoes and potatoes is used to validate this study. The accuracy of the proposed model is 98.44% on potato leaf samples.

Keywords: *CNN Model, Docker, POSTMAN API, TF Serving Server, Plant Village dataset.*

I. Introduction

A large portion of India's economy is based on agriculture. The employment rate for agriculture and allied industries is 70%. Increasing productivity and eliminating plant and food diseases are the two main objectives of agricultural research. Farmers are having a lot of problems as a result of modern plant diseases. Environmental pollution and climate change increase the susceptibility of several diseases in plants. People have begun producing crops in their home gardens and other areas as a result of increased knowledge of organic foods and crops. These plant illnesses are frequently constantly visible to farmers and other persons with unaided eyesight. The existing method for diagnosing illnesses in leaves is inadequate because the majority of foliar diseases have similar shapes, sizes, and colors. Below are the various reasons which show different reasons why detecting plant leaf disease is essential:

- Early Detection: Early disease detection in plant leaves is essential to stopping the spread of illnesses. Early discovery enables prompt response, which lowers the likelihood that a disease will spread to other plants and do substantial harm.

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- Crop Protection: Agriculture crops are susceptible to a number of illnesses that can drastically lower harvests. Early diagnosis and treatment of these diseases can help maintain crop production, providing a steady supply of food and farmers' financial security.
- Resource Optimization: Utilising resources like insecticides as well as more effectively is made possible by disease detection. Farmers can target impacted areas rather than randomly administering these herbicides, lessening the impact on the natural world while saving money.
- Environmental Conservation: Plant disease identification helps to conserve the environment by using fewer chemical treatments. With fewer substances in the environment, pollution is decreased and the damage to beneficial microbes is minimised.
- Increased Productivity: Crop quality and productivity are higher in productive, healthy plants. Increased agricultural output, which is crucial for feeding a growing world population, results from disease identification and management.
- Data-Driven Agriculture: Data-driven agriculture is getting more and more prevalent today. Making educated choices regarding crop management and disease control requires access to important data, which is provided by disease identification techniques like machine learning and remote sensing.
- Reduced Economic Loss: Plant ailments can cost farmers and the agriculture sector as a whole a lot of money. By enabling farmers to take action prior to the illness spreading and causing irreparable harm, early disease identification can help reduce these losses. [2-7]

The introduction of Computer Vision (CV), Machine Learning (ML), and Artificial Intelligence (AI) technologies has enhanced the creation of automated models enabling, accurate, and quick diagnosis of plant leaves disease. In the past ten years, several high-performance computer processors and devices have become available, which has greatly increased interest in AI and ML. In recent years, it has been evident that Deep Learning (DL) has primarily been used in agriculture. In this era of research, several deep learning architectures have been proposed by various authors. Among these, Convolutional Neural Network (CNN) is one of the most popularly deployed deep learning models. CNN is inspired by the biological nervous and vision system. It is an unsupervised deep-learning classification model having high classification and recognition accuracy. This model possesses a complex structure as it constitutes a large number of information processing layers. This multiple-layer architecture differs from the conventional Artificial Neural Networks (ANNs). Therefore, in this study, we propose a Convolutional Neural Network (CNN) for the classification of plant leaf disease. The performance of the model is validated on the images acquired from the Plant Village dataset.

The contributions of this research article are as follows:

- The use of ML and DL algorithms to identify plant diseases is discussed in this study in general terms. It offers a thorough grasp of the cutting-edge methods and techniques employed in this sector by reviewing studies published from 2015 and 2022.
- Datasets related to plant disease detection have been studied in the literature, including PlantVillage and Mendeley.
- The suggested method entails obtaining an input image, sending it to the model using the Postman API, using a CNN model housed inside a Docker container to analyse the image, and then producing a result to decide whether the image is classed as healthy or unhealthy.
- This study is validated using the Plant Village dataset, which includes data on plants like potatoes and tomatoes. On samples of potato leaves, the suggested model has a 98.44% accuracy rate.

II. LITERATURE SUTVEY

To increase the precision of the crop disease leaf recognition model, the VGG16 image feature extraction method is replaced with a depth residual network to extract deeper disease features and the bounding boxes are clustered using the k-means algorithm [1]. One of the main diseases that jeopardize the health of maize is northern maize leaf blight. A convolutional neural network-based approach to multi-scale feature fusion instance detection of maize leaf blight is suggested. It consists of three primary phases: preprocessing the data set, adjusting the network, and the identification mechanism.[2]. Pictures of unhealthy apple leaves with consistent and intricate backgrounds are gathered both in the lab and in the field to increase the robustness of the CNN model. Natural diseased apple photos are processed to produce enough training images using data augmentation technologies to address the issue of insufficient diseased apple leaf images and avoid excessive fitting of the CNN-based architecture during the training phase. To identify apple leaf illnesses in real time, a deep convolutional neural network is used. The suggested deep-learning-based solution can accurately recognize the distinguishing characteristics of the photos of damaged apples and recognize the five prevalent forms of apple leaf illnesses. [3].

The methods of image processing and machine learning with a precise algorithm are found for identifying tomato plant leaf illnesses. The samples of tomato leaves with diseases are taken into consideration in this inquiry. Farmers are able to detect infections depending on the early symptoms by using these disorder samples of tomato leaves. To enhance the integrity of the tomato samples, the samples of tomato leaves are first downsized to 256 256 pixels and then subjected to histogram equalization. For the purpose of dividing up data space into Voronoi cells, the K-means clustering is introduced [4]. The method for preventing the crop from suffering severe losses is discussed in this study. Because most diseases only affect the leaf region, it is where the internet is located. When an image has low contrast, histogram equalization is used to enhance the contrast before the K-mean clustering technique, which identifies items. Image processing techniques are utilized to properly identify illness in crop leaves and to study the disease for the benefit of the farmer's method which primarily consists of four steps—from the input RGB image color transformation structure [5].

The studies demonstrate how machine learning and deep learning methods can be used to precisely identify illnesses in potato plant leaves. Convolutional neural networks (CNNs) have been shown in numerous studies to accurately identify illnesses from unprocessed leaf photos. For instance, CNN models [6] that were 98.07% and 97.8% accurate, respectively. Similar to this, a sequential model based on CNN [7] that had a 94.2% accuracy rate. Other machine learning techniques have also demonstrated success in addition to CNNs.

Using a multi-class support vector machine (SVM) [8] obtained 97.56% accuracy. A SVM was also employed by Islam (2017), who achieved 95% accuracy. To achieve 95.99% accuracy, SVM [9] along with K-means clustering and grey level co-occurrence matrix (GLCM) feature extraction. Studies retrieved features from leaf photos in addition to using raw data to enhance model performance. Commonly extracted attributes were colour, texture, and form. For instance, extracted shape characteristics using leaf spot contour computations [8], texture features using GLCM, and colour features using RGB histograms. Latest machine learning algorithms use optical scans of potato leaves to automatically identify late and early blight illnesses. The PlantVillage Dataset was used to train four deep learning models, namely VGG16, VGG19, MobileNet, and ResNet50. In contrast with the various mathematical models, it is seen that VGG16 offers the highest accuracy (92.69%). Now, the model has been fine-tuned based on the idea of variable adjusting in order to further improve the efficiency of VGG16 [10].

The study on the identification of agricultural plant leaf diseases using image processing techniques [4] is presented and investigates automated disease classification and detection using computer vision and image analysis technologies. This review of the literature seeks to present an overview of the recent studies in the area of image-based plant leaf disease identification. The method [5] which offers a study on automated detection of maize plants infected with northern leaf blight using deep learning techniques, is the subject of this literature review. The authors create a system that is capable of precisely detecting and classifying the presence of northern leaf blight in maize crops using field photography and deep learning techniques. The survey seeks to give a summary of the research that has been done in this area. The system [11] by Johannes et al. proposes an automated plant disease diagnostic system using mobile capture devices, specifically applied to a wheat use case. The authors investigate the application of machine learning algorithms and image analysis techniques to create a reliable and effective system for diagnosing wheat illnesses. An overview of the current literature on automatic plant disease diagnosis utilizing mobile capture equipment is provided in this literature survey.

III. Methodology

The input for our proposed system is an image that is uploaded from either a PC or a mobile device. This study suggests a method for categorizing plant leaves with various disease infections that are inspired by convolutional neural networks. Table 1 is summarizing the details of results evaluated by various existing research.

Table 1. Comparison of different techniques to detect plant leaf disease.

Sr.No.	Reference	Algorithm	Dataset	Evaluation Metrics & Performance
1	[4]	K-means clustering (DWT + PCA + GLCM + CNN))	village database	Precision-0.995, Recall-0.995, Fscore-0.988, Accuracy-99.09
2	[12]	K-means clustering segmentation	PlantVillage and Mendeley	Precision- 0.904, Recall-0.905, Fscore-0.905 Accuracy-0.906
3	[13]	GCLM	PlantVillage	Accuracy-0.87 Fscore-0.87
4	[10]	VGG19, ResNet50, MobileNet and VGG16	PlantVillage	Accuracy-0.97
5	[14]	CNN	PlantVillage	Accuracy-0.82
6	[15]	Mask R-CNN	PlantVillage	Accuracy-0.933
7.	Ours	CNN	PlantVillage	Accuracy -0.9844

A. System Architecture

To create a scalable and efficient solution, the system design makes use of the Postman API, Docker containerization, a CNN model, and TensorFlow Serving. The suggested method entails receiving an input image, sending it to the model using a Postman API, processing the image using a CNN model stored inside a Docker container, and producing a result to determine if the image is classed as healthy or unhealthy. Figure 1 represents the architecture of the system. This architecture's modular and adaptable design makes it simple to integrate different components while providing reliable and robust image processing and categorization.

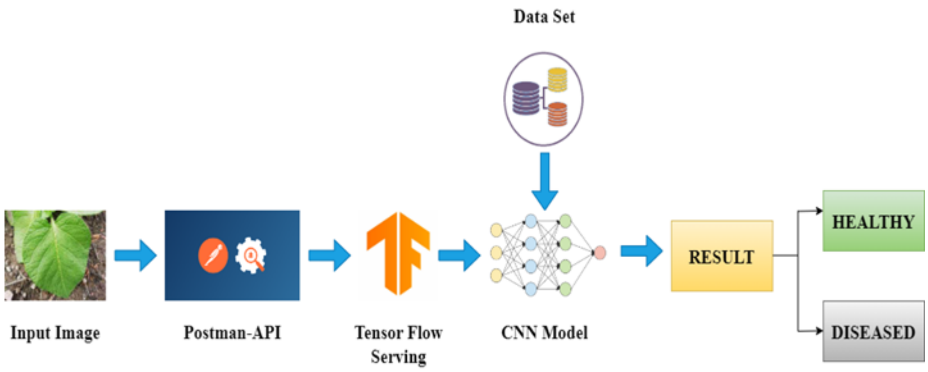


Figure 1. Proposed System Architecture

- **Input Image:** An image of a plant leaf that needs to be examined for the presence of disease is referred to as the input image. It acts as the system's main source of data input.
- **Postman API:** A platform for managing and creating APIs (Application Programming Interfaces), Postman API is a tool. The Postman API is utilized in this system design to handle the transfer of the input image from the user to the system's backend.
- **TensorFlow tf Serving:** An open-source serving system for machine learning models is called TensorFlow Serving. It offers an effective and scalable method for deploying trained models for inference. TensorFlow Serving is used in this system architecture to host the trained CNN model and serve predictions depending on the input image.
- **Trained CNN Model:** A deep learning model called the trained CNN was developed using data about plants. It has mastered the ability to spot patterns and traits in pictures of plant leaves that point to the presence of illnesses. The input image is analyzed by the CNN model, which makes predictions about whether the image will be labeled as healthy or not.
- **Plant Dataset:** The Plant Dataset Is a Collection of Labelled Photographs of Plant Leaves, Both Healthy and Those Suffering From Different Diseases. Using This Dataset, The CNN Model Is Trained to Identify the Traits of Healthy and Diseased Leaves and Generate Precise Predictions.

B. Flow Structure of Model

Figure 2 represents the model structure flow. The model's procedure starts with gathering photos, followed by pre-processing them to improve their quality, classifying them to reflect their content, and finally dividing the dataset into training and testing subsets for training and evaluation, respectively.

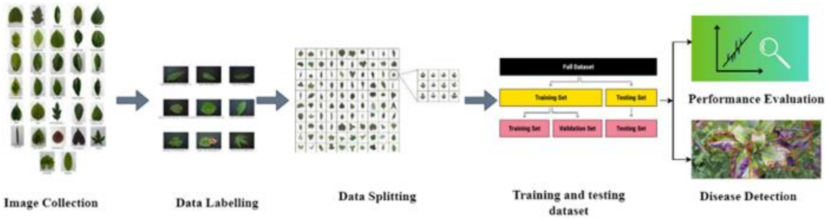


Figure 2. Flow Structure of Model

IV. RESULTS AND DISCUSSION

A. Dataset

In the suggested study, two database repositories have been used: one is a self-created dataset, and the other is the plantVillage dataset repository, which contains leaves from different plants. Plant leaves with the illness and plant leaves without it are represented in separate groups in these photos. According to the category, these photographs are categorized and given to the appropriate classes.

The illustration dataset in Figure 3. The images in Figure 3 were taken from the plantVillage dataset. The photos' specifics are displayed in Table 2.

Figure 3. Sample of images

Table 2. Details of Image categories

Image Type	Number of images
Potato Healthy	1011
Potato Diseased	1019
Tomato Healthy	1052
Tomato Diseased	1024

B. Pre-processing of images

Preprocessing of input images will lead to better and accurate generation of results. It si previously experienced in our last experimentation [16]. Before sending the photographs to the network, we resized them to the necessary size. To improve model performance, we also normalized the picture pixel value (keeping them between 0 and 1 by dividing by 256). This happens both during training and inference. We added a layer to our sequential model to cater to this. Data augmentation [17] is used to increase the quantity and quality of data. One of a data model's operations, cleaning data is crucial for high-accuracy models. However, if cleaning reduces the data's representability, the model cannot produce reliable predictions for inputs from the real world. Data augmentation techniques could make machine learning models more robust by generating variables that the model might meet in the actual world. Additionally, data augmentation aids in preventing model overfitting [18]. Figure 4 is representing changes to the images after preprocessing the input images.

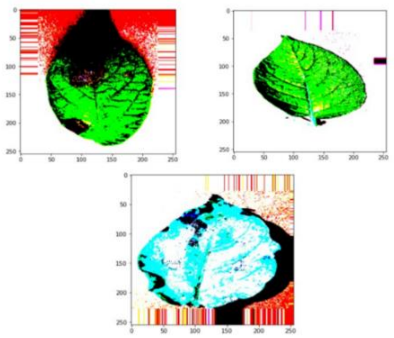


Figure 4. Image Preprocessing

C. Convolutional Neural Network

Due to the development of computationally efficient hardware like the Graphics Processing Unit (GPU), applications connected to deep learning have experienced exponential growth. The idea of deep learning was initially motivated by the conventional artificial neural network. The deep learning model has layered pre-processing layers that are used to extract data from the initial raw input to the final output that is task-specific to the task at hand.

CNN are the deep learning model used for challenging pattern recognition and classification problems with many datasets. The four primary layers of the model are convolution, max-pooling, fully-connected, and output layers [19]. These layers are stacked on top of one another. What distinguishes the design as innovative is its capacity to adapt itself in response to task-related results. CNN models like Alex Net, VGG, Google Net, Res Net, and others are available [21-22]. These models come in a variety of depths, configurations, nonlinear functions, and unit counts. As indicated in Table 3, the suggested technique makes use of a variety of layers and activation functions.

Table 3. Configuration Model

Name of Layer	Number of layers
Convolution Layers	6
Max Pooling Layers	6
Flatten Layer	2
Dense Layers	2
Activation Function	Relu

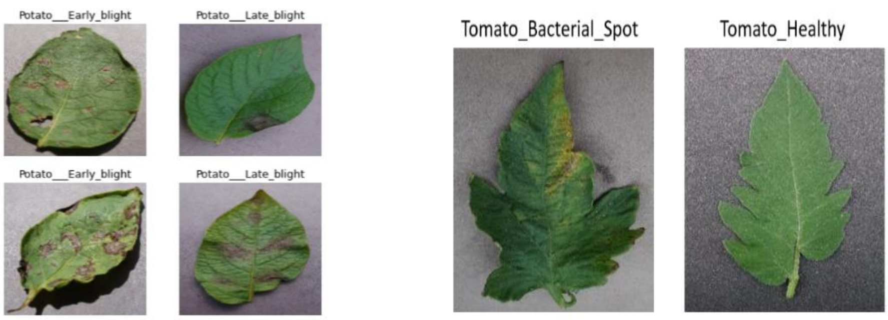
D. Training and Testing

The training, testing, and validation datasets were originally created from the entire dataset. To do this, the dataset is randomly split into training (80%), testing, and validation (10% each) groups. This ratio distribution is used in the majority of neural network applications. Training a CNN involves passing training data through it from input to output layers, making a prediction, and assessing the results or errors. The error is back-propagated from the topmost layer to the bottommost layer in reverse order if the forecast is incorrect. We use the backpropagation approach to gently alter the network weights to enhance the results. One epoch is considered to be this entire process. The stochastic gradient descent method is applied in this work to optimize the weights.

The suggested ternary classification model, based on convolutional neural networks, is then trained for the detection and classification of plant leaves, such as potato and tomato. In this ternary model, there are three possible outcomes: (i) classifying the given image as a plant leaf or not; (ii) classifying the image as a healthy plant leaf; and (iii) classifying the image as a sick plant leaf.

The training photos for each class label were collected with an image ratio of 80%. The remaining 20% of the photos did not change at all during the procedure. Each image from the normalized training dataset is fed into the convolution neural network model as an input to extract the features. This model predicts the class label for each training image.

The following graphic shows the sample photos that were utilized for training.



(a) (b)

Figure 5. Sample images for training model (a) Potato (b) Tomato

E. Experimental Results

The TensorFlow open-source software framework and the Python programming language were used to implement the training and testing procedures for the proposed model. Figure 6 shows the experimental results received after running the model. Accuracy is the performance metric [20] used for validating model.

Figure 6. Experimental results

The outcomes of the suggested methodology are primarily focused on:

1. The first step is to determine which plant's leaf is depicted in the photograph.

2. The next step is to determine if the image depicts a sick leaf or not.

3. If the image has a condition, identify the disease and suggest a suitable treatment.

4. If it is determined that the image is healthy, mark the response as such.

The accuracy of the testing of the disease prediction model is also shown in Figure 7. Figure 8 illustrates the calculated overall accuracy, which is 98.44%.

Testing the Model

```
In [25]: print("[INFO] Calculating model accuracy")
         scores = model.evaluate(test_ds)
         print(f"Test Accuracy: {round(scores[1],4)*100}%")

[INFO] Calculating model accuracy
8/8 [==============================] - 1s 15ms/step - loss: 0.0519 - accuracy: 0.9844
Test Accuracy: 98.44000000000001%
```

Figure. 7 Accuracy of the model

We have graphed the training and validation accuracy as well as the training and validation loss along with the accuracy. The training accuracy and validation accuracy are both growing, according to the accuracy graph. The loss graph for training and validation demonstrated a reduction in loss over time.

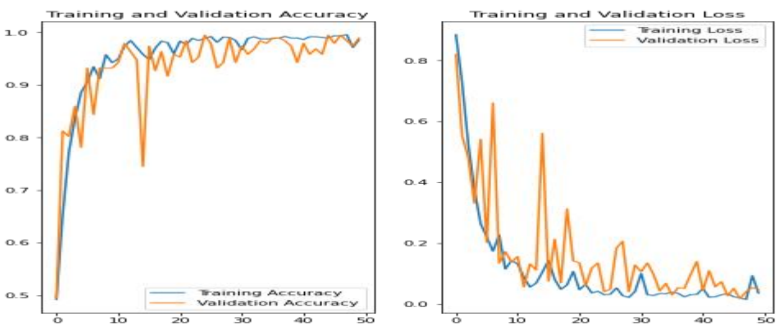


Figure 8. Accuracy and loss graphs

V. CHALLENGES

Due to a number of circumstances, detecting potato leaf diseases can be difficult. Resolving these issues is essential for efficient disease control in potato agriculture. The following are some of the main obstacles to identifying potato leaf diseases as shown in figure no 9.:

- Symptom Variation: Potato leaf diseases can present in a variety of ways, and the symptoms may differ based on the pathogen species, the surrounding environment, and the potato variety. Due to this variety, it may be challenging to correctly diagnose diseases based merely on their visual symptoms.
- Early Detection: Early diagnosis is essential for illness treatment since it enables prompt intervention to stop the disease's progress. The early stages of numerous illnesses, however, might not be accompanied by obvious symptoms, finding it difficult to detect them before they pose a serious threat.
- Pathogen Diversity: Fungi, microbes, and virus are just a few of the pathogens that can cause leaf diseases in potatoes. Different detection techniques may be needed for each infection, and often several pathogens may co-infect the same plant, making diagnosis even more challenging.
- Environmental Factors: Temperature and humidity are two environmental factors that might affect how a disease develops and how its symptoms manifest. This means that different growing seasons or geographical locations may not have the same illness symptoms.
- Limited Diagnostic Expertise: Many potato growers may lack access to plant pathology expertise, which is frequently necessary for effective disease identification. Particularly in distant or resource-constrained places, training and access to professionals can be restricted.
- Cost of Diagnostic Tools: Some advanced diagnostic tools, such as DNA-based tests or molecular techniques, can be costly and require specialized equipment. Small-scale or resource-limited farmers may not have access to these tools.
- Data Collection and Analysis: It might take a lot of time and effort to collect and analyse data on the prevalence and severity of diseases. To increase the effectiveness of this procedure, automation and data processing techniques are required. [9-15]

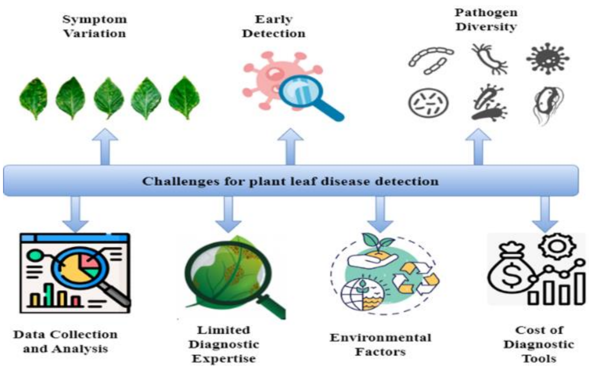


Figure 9. Challenges faced while detecting plant leaf disease.

VI. CONCLUSION AND FUTURE WORK

The convolutional neural network was employed in this study to detect disease in tomato and potato leaf tissue. Agriculture's arduous task of crop protection calls for an in-depth understanding of both the crop being grown and any pests. The developed program deals with the problem of manually detecting non-real-time plant leaf diseases. The experiment demonstrates the application of CNN to detect plant diseases in controlled situations. According to the test, CNN operated outside of real-time and yet managed to attain 98% accuracy. CNN and leaf photos are used to identify plant illnesses and their cures. The suggested method involved many steps, including disease detection, data augmentation, and data processing.

Data preprocessing was done largely to improve the accuracy of detection and reduce the negative effects of high-intensity light on image recognition. Data augmentation was used to improve the performance of the model by introducing new cases for underrepresented classes, balancing the dataset, and preventing overfitting.

The study's model was successful in detecting leaf disease. Due to its effectiveness and accuracy, the illness detection model could replace human specialists' on-site identification. While eliminating the subjective character of feature selection, might reduce labour. Using different algorithmic pairings to more precisely identify plant diseases could further enhance this method. We may experiment with additional commercially relevant plants in the future to assess the disease severity while also taking into consideration other plant components.

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